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# Improvement of Rule Generation Methods for Fuzzy Controller

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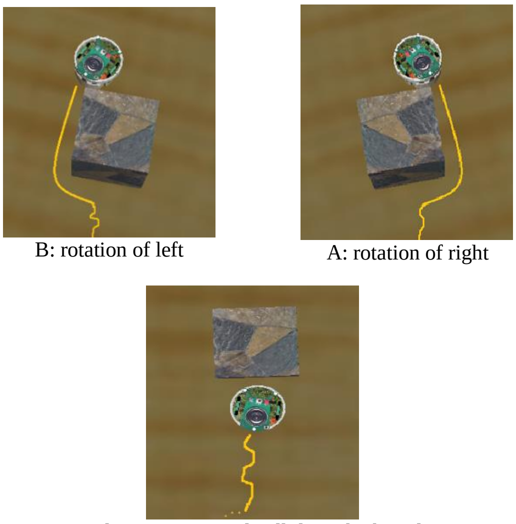
**Abstract**
This paper proposes a fuzzy modeling using the data obtained. The fuzzy system is known as a knowledge-based or rule-based system. The most important part of the fuzzy system is rule-base. One of the problems of generation of the fuzzy rules using the training data is the inconsistency of the data. Existence of inconsistent and uncertain states in training data causes a high error in modeling. Here, the probability fuzzy system is presented to improve the above-mentioned challenge. A zero-order Sugeno fuzzy model is used as the fuzzy system structure. At first, using clustering, the number of rules and input membership functions is obtained. A set of candidate amounts is considered for the consequent parts of the fuzzy rules. Considering each pair of training data, the probability of the consequent candidates is changed. In the next step, the eligibility probability of each consequent candidate is determined for all rules. Finally, using the probabilities obtained, two probable outputs are generated for each input. The experimental results obtained show the superiority of the proposed approach over some available well-known approaches that reduce the number of rules and reduce the system complexity.

**Keywords:** *Fuzzy Controller, Fuzzy Rule Generation, Inconsistent Training Data.*

## 1. Introduction

Lotfi Zadeh, professor of University of Berkeley in America presented a collection of fuzzy [1] and fuzzy controllers [2] in 1965 and 1973. Fuzzy systems are knowledge-based or rule-based systems. The most important part of a fuzzy system is its fuzzy rule base. There are different methods used for generating fuzzy rules [3-5] such as the look-up schema [3] so fuzzy systems are universal approximation [6, 7]. Fuzzy systems have been used in a wide range of fields [8-13]. One of the methods used for generation of fuzzy rules is the look-up table. In this method, each input-output data is generated as a fuzzy rule so there is inconsistency among the data so as to select the rules with the highest degree between all the consistent rules. In this method, the systematic procedure is not used to determine the number of fuzzy rules and member functions that are independent from the input data. Many methods are like to look up that they are use form maximum for selected of rule and so are use different solution like genetic algorithm for tune parameter of system, weakness of other of this method is constant of number of rule [14]. Another proposed method, designing fuzzy system that is based on the descend gradient [15, 16], in the method input-output data is influenced on parameters. Other method is clustering of input-output data that each of cluster is considered as one rule [16]. Advantage of this method is variable number of rules. Weakness of this method is loss of right solution in front of inconsistence data because whatever clusters be smaller, there is inconsistence problem. some methods only use input clustering [17]. It is better input-output clustered together until used to be the knowledge contained in the output data. Other method that using numerical data in designed fuzzy system is grouping of inconsistence data method [5] that to inconsistence data existent in one group related to probability. Finally, with weighted averaging of output of rules are obtain final output of system. The most methods that are improved inconsistence problem by used the averaging that is increased system error. For example, when output data are $+45^{\circ}$and $-45^{\circ}$averaging makes output data equal to zero and it is big error. According figure 1 when $+45^{\circ}$ (part A) and $-45^{\circ}$ (part B) considered as rotated angle of robot in robot navigation and robot is facing with an obstacle, robot will collide with obstacle [18].



B: rotation of left

A: rotation of right

C: direct motion and collide with obstacle

**Figure 1. Bad influence of inconsistency in training data.**

In other method [19,20] is used grid partition so number of fuzzy rule and as complexity is increased.

In the paper, we design of fuzzy system with clustering, fuzzy system of zero order Sugeno [21] and a set of candidate amounts for consequence part of fuzzy rules. In most methods to considered only one candidate in consequence part that the probability of error in inconsistency will crease [22]. In the study, a new method is proposes to improving mentioned methods by using the probability fuzzy rules. To optimize the number of rules is uses to the clustering method and to improve the inconsistent problem is uses to probability of fuzzy rules. The rest of paper is organized as follows. In section 2, we present probability fuzzy rules and a new method for to generate probability output of fuzzy system. In section 3, the new method is evaluated and in section 4, the conclusion is given.

## 2. Generate probability fuzzy rules

In this paper, we propose an approach to design probability fuzzy systems. This method is called Generation of Probabilistic Fuzzy Rules (GPFR).

**Step1:** Clustering input-output data

In paper is used FCM [23, 24] for clustering input-output data. Fuzzy c-means is one of the methods clustering which allows data to belong to two or more clusters but in non-fuzzy clustering, data is split into separate clusters where each data can belong to exactly one cluster. Input-output data are clustered together.

**Step2:** Define fuzzy sets

Suppose that $s = x_1 \times \ldots \times x_n$ is, input n dimension variable and $A_i = A_{i1} \times \ldots \times A_{in}$ is $n$ fuzzy sets witch are required to be complete. Each cluster has n Gaussian function that Gaussian functions of *i'th* dimension of each cluster must be in one set.

Expert can merge member function with large overlap and change number of member function. Figure 2 illustrates one fuzzy set with large overlap and figure 3 show modified member function.

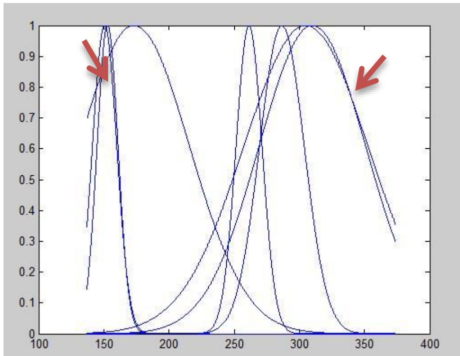



**Figure 2. Membership function before merge.**

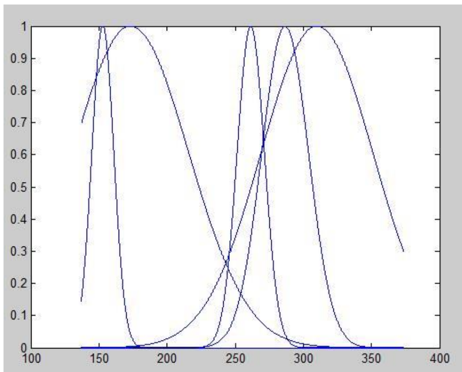



**Figure 3. Membership function after merge.**

$m$ is number of discrete action for any rule and $action_{ij}$, candidate action j for rule $i$ and $p_{ij}$ probability value of action j in rule $i$. Appropriate action is selected in any rule of the m action and for output of fuzzy system, calculated weighted combination of theirs.

**Step 3:** Determine structure of fuzzy system

The fuzzy rules construct with input-output data as follow:

$$\begin{aligned} &Rule_i: if\ x_1\ is\ A_{i1}\ and\ x_2\ is\ A_{i2}\ and\ \dots\ x_n\ is\ A_{in},\ then \\ &o_{i1}\ is\ action_1\ with\ probability\ p_{i1}\ and \\ &o_{i2}\ is\ action_2\ with\ probability\ p_{i2}\ and \\ &\dots \\ &o_{ik}\ is\ action_m\ with\ probability\ p_{im} \\ &\textstyle\sum_{j=1}^{m} p_{ij} = 1,\ i = 1, \dots, c \end{aligned} \tag{1}$$

Where $x_i$(i=1,2,...,n) are input variables,$o_{ik}$ is the candidate action, and $A_{ij}$ is linguistic terms of input variable $x_j$ in rule $R_i$ .

**Step4:** Adjust the parameters of consequence the rules with probability values

In the first, $p_{ij}$ is zero-initialized. The output data of one cluster compared with candidate action in consequence of rule. In each cluster to output data of one cluster compared with candidate actions, degree of membership ($U_{ki}$) of data add to $p_{ij}$ nearest candidate action and in the end probability values are normalizes.

$$p_{ij} = \frac{\sum_{|output_k - action_j| < |output_k - action_{t \neq j}|}^{k} U_{ki}}{\sum U_{ki}} \tag{2}$$

i=1:c, j=1:m,

k=1:n' (n'=number of data in cluster$_i$)

**Step5:** consider the appropriate policy

To improvement inconsistency in fuzzy rules, two probabilistic outputs considers instead of one probability output. Since there is a set of candidate amounts for consequence parts of fuzzy rules, only one candidate amount should choose between candidates. Since there are two output in final output fuzzy system, for first output of each rules, candidate related with maximum probability should be greedily chosen and by (5) first final output is obtained. In this output, there is probability that be obtained from multiplying maximum probability of each candidate amount rules by (3).

$$\mathrm{p1} = \prod_{i=1}^{c} \max(p_{ij})\ ,j = 1{:}\,k \tag{3}$$

To calculate second output and its probability a criteria should be consider. This output should choose with two conditions: high probability and to be different in comparison with all first output members as following equation:

$$\mathrm{p2} = \prod_{i=1}^{c} \max(\mathrm{p_{in}})\ , \tag{4}$$

$n \neq j$ is selected output1

For example, first and second outputs are selected as follows in figure 4 and figure 5, respectively from probability consequence part.

| | | | | |
|---|---|---|---|---|
| 0.0011 | 0.0541 | 0.2838 | 0.6418 | 0.0191 |
| 0.0369 | 0.1028 | 0.3210 | 0.5185 | 0.0208 |
| 0.0163 | 0.0208 | 0.2045 | 0.7260 | 0.0324 |
| 0.0517 | 0.0601 | 0.0574 | 0.7475 | 0.0833 |
| 0.1169 | 0.2068 | 0.2753 | 0.3758 | 0.0252 |

**Figure 4. First output of each rule.**

| | | | | |
|---|---|---|---|---|
| 0.0011 | 0.0541 | 0.2838 | 0.6418 | 0.0191 |
| 0.0369 | 0.1028 | 0.3210 | 0.5185 | 0.0208 |
| 0.0163 | 0.0208 | 0.2045 | 0.7260 | 0.0324 |
| 0.0517 | 0.0601 | 0.0574 | 0.7475 | 0.0833 |
| 0.1169 | 0.2068 | 0.2753 | 0.3758 | 0.0252 |

**Figure 5. Second output of each rule.**

**Step 6:** Determine the fuzzy system output

This method is proposed one probability distribution function and in output can obtain probability output.

The output of Sugeno fuzzy system [21] calculates following equation:

$$\hat{y}_{index} = \frac{\sum_{i=1}^{c} w_i output_i}{\sum_{i=1}^{c} w_i}, index = 1,2 \tag{5}$$

First output symmetrical with action selection in *p1* and for second output symmetrical with action selection in *p2*.

The weight of each rule calculates as follows:

$$w_i = \prod_{j=1}^{k} \mu(A_i^j) \tag{6}$$

$\mu(A_i^j)$, is the degree of membership function and describe by following equation:

$$\begin{aligned} &\mu(A_j^i) = \exp\left(-\frac{1}{2}\frac{(x_j - v_{ij})^2}{\sigma_{ij}}\right) \\ &i = 1, \dots, c \\ &j = 1, \dots, k \end{aligned} \tag{7}$$

$\sigma_{ij}$,$v_{ij}$, represent the center and width of the membership function, respectively.

Pseudocode of generation of probability fuzzy rule is described in figure 6.

$(x_n, y_n)$ classified in c cluster with c-means cluster
Initialize $p_{ij}$ with zeros (i=1:c)
Foreach $(x_p, y_p)$, $x_p$ is input and $y_p$ is output
If $(x_p, y_p)$ is member cluster i

1. $p_{ij} = p_{ij} + U_{ip}$ ($U_{ip}$ is member degree $(x_p, y_p)$ to $cluster_i$ , $action_j$ *is nearest* action to $y_p$)

End
End

Normalized $p$

Action selection from each rule for output1
Foreach $rule_i$
$action_j$ selected from $rule_i$ with max probability
End
Action selection from each rule for output2
Foreach $rule_i$
$action_{j'}$, selected from $rule_i$ with max probability, $action_j \neq action_{j'}$
End

**Figure 6. Pseudo code of generation of probability fuzzy rule.**

## 3. Experimental set-up

Data set is shown in table 1. The Concrete slump test data set is obtained from the UCI machine-learning repository [25]. This repository is a collection of databases and data generators that are used in the machine learning field for experimental analysis of machine learning algorithms. The geyser data set was obtained from a website and it describes the waiting time between two index: eruptions and the duration of eruptions for Old Faithful in Yellowstone national park. The E-puck robot data collected by Webots.

**Table 1. Summary description for the data sets of the study.**

| Data Set | Number of examples | Number of attributes |
|---|---|---|
| Concrete slump | 103 | **7** |
| Geyser | 272 | 1 |
| E-puck Robot data | 2791 | 4 |

To evaluate the prediction accuracy of presented method for the data sets a 10-fold cross validation is used. For each simulated experiment, ten trails are used for each real data set, and 100 trails are used for each simulated experiment.To evaluate a test set , the mean Squared between the observed, $y^i$, and estimated, $\widehat{y^i}$, outputs are defined as following equation:

$$MSE = \frac{1}{n} * (y_i - \hat{y_i})^2 \quad (8)$$

To evalute the performance accuracy of proposed method, it is compared with probability fuzzy method (PFM) [5] and look-up scheme(Wang and Mendel approach(W-M)) [3] and results shown in table 2 as results of 100 trails used for each simulated experiment are shown in figure 7, figure 8, figure 9.

**Table 2. Prediction accuracy over three experiments.**

| Data Set | PFM | GPFR | W-M |
|---|---|---|---|
| Concrete slump | 64.06 | 26.16 | 66.4 |
| Geyser | 34.11 | 13.06 | 56.45 |
| E-puck Robot data | 488.91 | 412.51 | 716.79 |

By considering two output of fuzzy system, the error decreased in GPFR method because in the method is used from clustering input-output for generation of fuzzy rules as have reduce complexity in designed system and number of rules in this method less than others witch is shown in table 3.

**Table 3. Number of fuzzy rule.**

| Data Set | PFM | GPFR | W-M |
|---|---|---|---|
| Concrete slump | 50 | 8 | 50 |
| Geyser | 5 | 3 | 5 |
| E-puck Robot data | 28 | 5 | 28 |

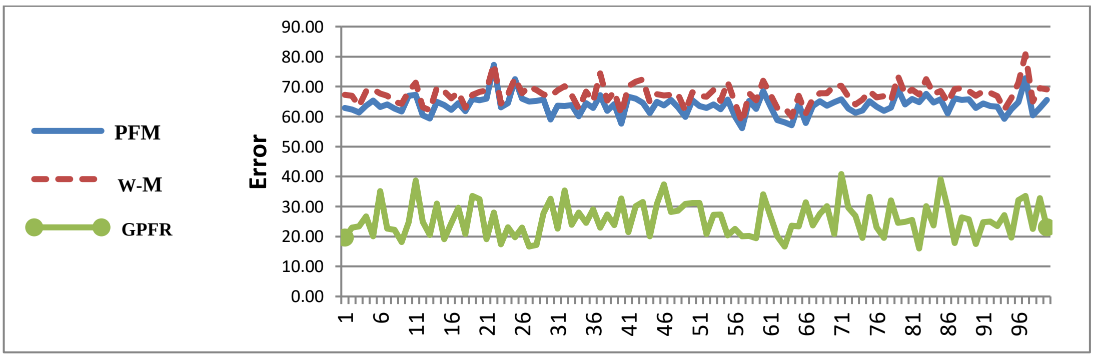



**Figure 7. Error in Concrete slump.**

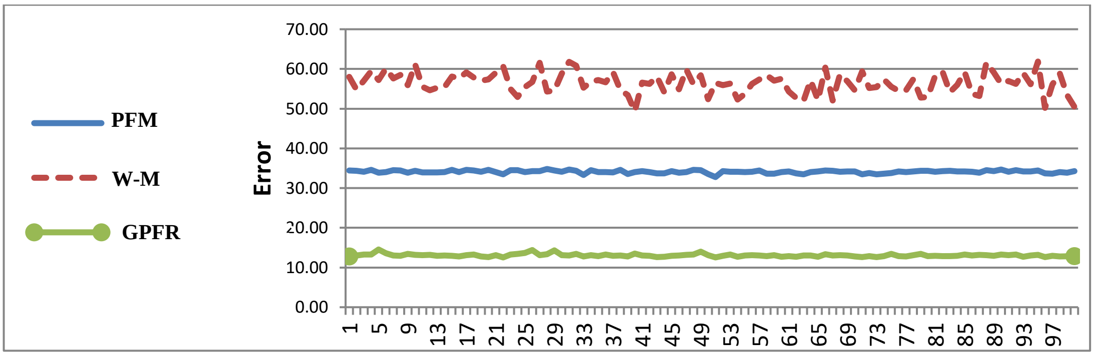



**Figure 8. Error in Geyser.**

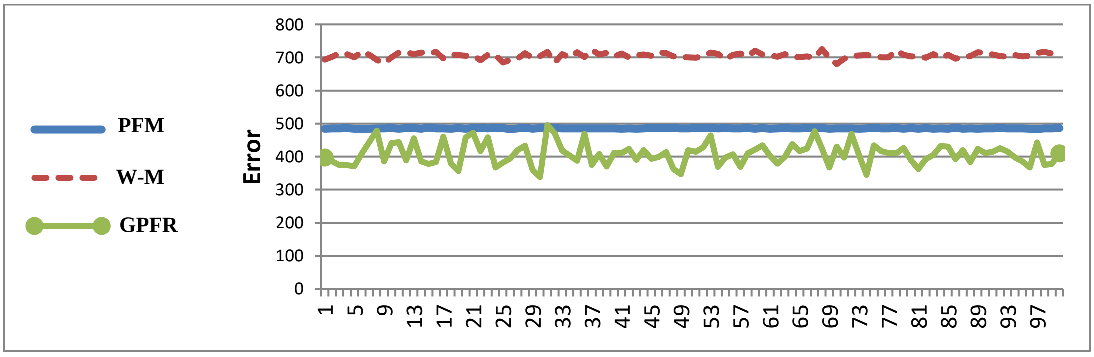



**Figure 9. Error in E-puck Robot data.**

## 4. Conclusion

In this paper a new method was proposed for generation probability fuzzy rules. Since in inconsistent condition there are several rules with similar IF part and different consequence part,we proposed a approach to generate a fuzzy system as a probability distrbution function. The clustering was used to determin the input membersip functions of fuzzy rules and conseequence part of rules are probablistic. Comparisions ,indicate cluster is usefule to decrease fuzzy system complexity as well as the results outperformed the last related approaches.

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